

Misleading News Classifier

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By

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DECLARATION

I, **Anu Kumari**, D/O **Dharmendra Kumar**, declare that my project entitled “**Misleading News Classifier**”, submitted at **School of Data Science, Asian School of Media Studies, Film City, Noida**, for the award of **B.Sc. in Data Science, Noida International University and Graduate** is an original work and no similar work has been done in India anywhere else to the best of my knowledge and belief.

This project has not been previously submitted for any other degree of this or any other University/Institute.



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Abstract

False or Misleading News Classifier that is presented as news is known as fake news. Human behaviour affects people's propensity to disseminate misleading information; studies show that people are drawn to novel and unexpected information and events because they stimulate different parts of their brains. Furthermore, motivated thinking was shown to contribute to the dissemination of false information. This ultimately motivates people to share or repost misleading content, which is usually recognised by attention-grabbing titles and click-bait. The suggested study employs natural language processing techniques to distinguish false news—more precisely, fraudulent news items originating from dubious sources. This dataset, called –dataset name-, is made up of real and fake news that has been gathered from a variety of sources. In order to gather the most recent news and add it to the dataset, web scraping is utilised in this instance to extract text from news websites. Pre-processing the data and feature extraction are applied. Next comes the reduction of dimensionality and classification utilising models such the Gradient Boosting classifier, Bagging classifier, Passive Aggressive classifier, and Rocchio classification. We examined several algorithms to determine which model had the best functioning prediction for bogus news.

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MISLEADING NEWS CLASSIFIERS

CHAPTER-1

I. INTRODUCTION

1.1.1 Background

The world is quickly changing. There are undoubtedly many benefits to living in a digital age, but there are drawbacks as well. This digital environment presents a variety of challenges. Fake news is one of them. Fake news is easily disseminated by someone. Spreading false information is done with the intention of damaging someone's or an organization's reputation. It might be propaganda used to discredit an organisation or political party. A person can disseminate false information on a variety of internet sites. This covers social media sites like Facebook and Twitter, among others. Within artificial intelligence, machine learning is the component that facilitates the creation of systems with the ability to learn and execute various tasks (Donepudi, 2019). Supervised, unsupervised, and reinforcement machine learning algorithms are among the many types of machine learning algorithms that are accessible. An initial train data set must be used to hone the algorithms. These algorithms are capable of carrying out a variety of tasks following training. There are several industries that use machine learning for a variety of purposes. Machine learning techniques are typically employed in predictive maintenance or for concealed object detection. Online platforms are advantageous to users since they provide easy access to news. However, this presents a risk because it allows hackers to use these platforms to disseminate false information. There is evidence that this news is detrimental to individuals or society. After reading the news, people begin to believe it without checking. It is difficult to identify fake news, which makes it a significant difficulty (Shu et al., 2017). Fake news can spread quickly if it is not identified, at which point everyone will begin to believe it. Fake news has the potential to affect people, groups, or political parties. In the US Election of 2016, fake news has an impact on

people's opinions and decisions. Various researchers are trying to identify false information. In this sense, machine learning is showing to be beneficial. Various algorithms are employed by researchers to identify fraudulent news. According to researchers in Wang (2017), identifying fake news is extremely difficult. They have employed machine learning to identify false information. According to research by Zhou et al. (2019), fake news is growing more prevalent over time. For this reason, it's important to identify false news. Machine learning algorithms are trained with this goal in mind. After they have been educated, machine learning algorithms will automatically recognise bogus news.

1.1.2 Problem Statement

Develop a machine learning-based system capable of accurately detecting fake news articles. The system should be able to analyze and classify news content in real-time, distinguishing between legitimate news and fake news with high accuracy. The goal is to create a scalable, efficient, and reliable model that can be integrated into various digital platforms to help curtail the spread of misinformation.

1.1.3 Motivation

Detecting fake news is crucial for several reasons. First and foremost, it plays a vital role in preserving the truth. Fake news distorts reality, spreading misinformation and disinformation, which can have far-reaching consequences. By actively identifying and countering fake news, we can ensure that people have access to accurate information, thus preserving the integrity of public discourse. Moreover, in democratic societies, an informed citizenry is essential for effective governance. Fake news can manipulate public opinion and undermine the democratic process. Detecting and

combating fake news is therefore crucial for safeguarding the integrity of democratic institutions and promoting a healthy democracy.

Additionally, fake news detection is essential for the prevention of harm. Fake news has the potential to incite panic, violence, or harm to individuals and communities. By identifying and debunking fake news, we can mitigate these potential harms and protect vulnerable populations. Furthermore, the proliferation of fake news erodes trust in traditional media outlets and reputable sources of information. Media organizations can demonstrate their commitment to journalistic integrity and regain public trust by actively working to detect and combat fake news.

Teaching people to critically evaluate information they encounter online is an essential skill in the digital age. Detecting fake news provides an opportunity to educate individuals about media literacy and the importance of verifying sources. By promoting critical thinking skills, we can empower individuals to navigate the complex media landscape more effectively. Lastly, fake news often seeks to divide communities along ideological, political, or cultural lines. By identifying and exposing fake news, we can promote social cohesion and foster a more united society. Overall, the motivation for fake news detection lies in its potential to protect truth, democracy, public safety, trust in media, critical thinking skills, and social cohesion.

1.1.4 Objectives

The primary objective of this project is to develop a robust machine learning-based system that can accurately detect fake news articles. The

system should be able to analyze and classify news content in real-time, distinguishing between legitimate news and fake news with high precision and recall. This involves several specific goals:

Data Collection and Preprocessing:

1. Gather a diverse and comprehensive dataset of labeled news articles from credible sources.
2. Preprocess the text data by cleaning, tokenizing, stemming/lemmatizing, and removing noise to prepare it for feature extraction.

Feature Engineering:

1. Use natural language processing (NLP) techniques to extract meaningful features from the text, including word embeddings (e.g., Word2Vec, GloVe, BERT) and TF-IDF scores.
2. Incorporate additional features such as article metadata (e.g., publication date, author information), source reliability, and social engagement metrics.

Model Development and Training:

1. Train various machine learning models (e.g., logistic regression, support vector machines, decision trees) and deep learning models (e.g., LSTM, BERT) to classify news articles.
2. Perform hyperparameter tuning and cross-validation to optimize model performance and ensure robustness.

Model Evaluation and Validation:

1. Evaluate the performance of the models using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC.
2. Use confusion matrices and other diagnostic tools to analyze and understand the types of errors made by the models.

Deployment and Real-Time Detection:

1. Develop a scalable deployment pipeline that allows the system to process and classify news articles in real-time.
2. Create a user-friendly interface or API for easy integration with various digital platforms and applications.

Continuous Monitoring and Improvement:

1. Implement monitoring and logging mechanisms to track the system's performance over time.
2. Regularly update the model to address concept drift and adapt to new patterns and tactics used in the dissemination of fake news.

By achieving these goals, the project aims to create an effective tool for detecting Misleading news, thereby contributing to a more informed public, enhancing trust in digital news platforms, and supporting the integrity of information in the digital age.

1.1.5 An outline of the project

A news dataset.csv was purchased which in turn had two sorts of news inside itself that was labelled as True news and Fake news .Python code that uses machine learning techniques like linear aggression, decision tree classification, gradient boost classification, and random forest classification has been run using Jupyterlab.TfidfVectorizer was used in the application to identify the word frequency scores and it will tokenize documents, learn the vocabulary and inverse document frequency weightings and allows the user to encode new documents.

2 Literature Review

2.1 Overview

In an effort to detect fake news, a number of measures have been implemented: In 2018, a study report on detecting fake news was published by three students from the Vivekanand Education Society's Institute of Technology in Mumbai[2]. The research paper they published stated that the social media era began in the 20th century. Web traffic eventually rises together with the quantity of posts and articles published. Artificial intelligence, machine learning, and natural language processing (NLP) approaches were among the tools and strategies they employed to identify fake news[7].

According to an article, Facebook and WhatsApp are also focusing on detecting bogus news. They've been working on it for almost a year, and the alpha phase is happening right now. A student from Ho Chi Minh City University of Technology (HCMUT) in Cambodia named Nguyen Vo conducted research on the identification of fake news and put it into practice in 2017. In his effort on fake news identification, he employed the Bi-directional GRU with Attention mechanism, which was first put forth by Yang et al[2]. Along with using various deep learning algorithms, he also attempted to use other deep learning models, including CNN, GAN, and auto-encoders.

Stanford University's Samir Bajaj released a study on the identification of fake news. Using an NLP approach, he identifies bogus news and applies other deep learning algorithms. He used real data from the Signal Media News dataset. Following the massively popular fake news of recent times, various methods have been developed to identify fake news[5]. Social bots, trolls, and cyborg users are the three categories of people who contribute to fake news. A social media account that is managed by a computer algorithm is called a "social bot," according to Social Bots. Content can be created automatically by the social bot. Furthermore, it should be noted that trolls are actual people who "aim to disrupt online communities" in an effort to elicit an emotional reaction from social media users. Cyborg is the other one.

Users of cyborgs combine "automated activities with human input[4]."To engage in social media activities, people create accounts and use programmes. Support vector machines (SVM) and the Naïve Bayes classifier are the approaches most frequently employed to perform these kinds of tasks.

3. Definitions And Details

3.1 Data Preprocessing

Social media data is largely unstructured; most of it consists of casual conversations with misspellings, slang, poor grammar, etc.

The need to improve performance and dependability has made it essential to create strategies for resource utilisation so that decisions can be made with knowledge. The data must first be cleaned before it can be used for predictive modelling in order to produce better insights. Basic pre-processing was applied to the News training data for this reason.

This stage involved cleaning the data.

Both structured and unstructured data are obtained throughout the reading process. While unstructured data lacks a proper framework, structured formats have clearly recognised patterns. We have a semi-structured format that falls in between the two frameworks and is more structured than unstructured.

To identify qualities that we want our machine learning system to recognise, the text input must be cleaned up. A number of stages are usually involved in cleaning (or pre-processing) the data:

a.Eliminate all punctuation.

Punctuation can give a sentence grammatical context that enhances our comprehension. However, since our vectorizer just counts the words in a

sentence rather than their context, it adds no value, therefore we eliminate all special characters. like as: How are you? -> How are you?

b.The Token System

Text is tokenized such that it is divided into words or sentences. It gives previously unstructured text organisation. For example: Plata o Plomo -> "Plata," "o," "Plomo."

c.Eliminate stopwords

Slang terms that are often used in texts are known as stopwords. As a result of their lack of information, we have deleted them. For example: I don't mind lead or silver; lead, great.

d.Stemming

Reducing a word to its stem form is aided by stemming. Treating related words similarly makes sense most of the time. It eliminates suffices using a straightforward rule-based method, such as "ing," "ly," "s," and so on. Although the word corpus is decreased, the words themselves are frequently overlooked. For example: Entitled -> Entitling. Note: Words with the same stem may be treated as synonyms by certain search engines.

3.2 Feature Generation

Numerous features, such as word count, frequency of large words, frequency of unique words, n-grams, etc., can be produced from text data.

We can make it possible for computers to comprehend text and carry out tasks like clustering and classification by building a representation of words that captures their meanings, semantic links, and the many contexts in which they are used.

Vectorizing Data: In order to construct feature vectors that machine learning algorithms can grasp our data, the process of vectorizing involves encoding text as integers, or in numerical form.

1. Vectorizing Information: Word Bag

Count or Bag of Words (BoW) The vectorizer characterises the words that are present in the text data. If it appears in the sentence, it returns a score of 1, and if not, it returns a score of 0. Consequently, it generates a word bag for every text document based on the document-matrix count.

2. N-Grams for Vectorizing Data

N-grams are just all possible permutations of neighbouring words or letters of length n that we can locate in our original text. Unigrams are ngrams when n = 1. In the same way, you can use trigrams (n=3), bigrams (n=2), and so forth. In contrast to bigrams and trigrams, unigrams typically don't hold as much information. N-grams work on the basic premise of capturing the letter or word that is most likely to come after the supplied word.

3. Data Vectorization: TF-IDF

It calculates a word's "relative frequency" within a document by comparing its frequency within all documents. The relative importance of a phrase inside the document and the full corpus is represented by its TF-IDF weight. "TF" represents "Term Frequency": It determines the number of times a term occurs in a given document. A term may appear more frequently in a long text than in a short one because every document size differs. As a result, term frequency is frequently divided by document length.

Note: Used for document clustering, text summarization, and search engine scoring.

$$(Word-frequency-in-given-document) \cdot \log \frac{(Total-number-of-documents)}{(Number-of-documents-containing-word)}$$

3.3 Algorithms used for Classification

Logistic Regression

The sigmoid function, which accepts input as independent variables and outputs a probability value between 0 and 1, is used in logistic regression for binary classification.

For instance, we have two classes: Class 0 and Class 1. An input falls into Class 1 if its logistic function value is greater than the threshold value of 0.5, and it falls into Class 0 otherwise. Because it is a continuation of linear regression and is primarily applied to classification difficulties, it is known as regression.

Linear Regression

Linear regression is a simple statistical method used to understand and predict the relationship between two variables. Imagine you want to predict someone's height based on their age. Linear regression helps you find a straight line that best fits the data points, showing how height tends to change as age increases. This line is represented by an equation, like $y = mx + b$, where y is the height, x is the age, m is the slope (how much height changes with age), and b is the y-intercept (the height when age is zero).

This method is widely used because it's straightforward and easy to interpret. You can apply it to various situations, like predicting house prices based on size or sales based on advertising spend. However, it works best when the relationship between variables is roughly a straight line and doesn't handle complex patterns well.

Support Vector Machine

A supervised learning machine learning approach called "Support Vector Machine" (SVM) can be applied to problems involving

regression or classification. Nonetheless, it is mostly applied to classification problems, such text classification. Each data item is plotted as a point in n-dimensional space (where n is the number of features you have) using the SVM algorithm. The value of each feature is represented by a specific position. Next, we carry out the classification process by identifying the ideal hyper-plane that effectively separates the two classes (please refer to the screenshot below for an example).

Random Forest

Random Forest is a popular machine learning technique used to make accurate predictions. Imagine you have a group of experts, and you ask each one to make a prediction. Then, you combine all their predictions to get a final answer. This is essentially how Random Forest works. It creates many decision trees, which are like flowcharts where each question (or decision) leads to another question or a final answer. Each tree makes its own prediction, and then Random Forest combines all these predictions to give the final result. This approach makes the predictions more accurate and reliable because it averages out the errors of individual trees.

Random Forest is great because it can handle a lot of data and different types of information. It works well for both classification tasks (like deciding if an email is spam or not) and regression tasks (like predicting house prices). Plus, it's good at handling missing data and doesn't overfit easily, meaning it performs well on new, unseen data.

CHAPTER-2

METHODOLOGY

2.1 Introduction

The methodology for fake news detection begins with comprehensive data collection from diverse sources, including social media platforms like Twitter and news websites. This data is acquired through APIs, web scraping, or manual collection, followed by preprocessing steps to clean and standardize the text. Feature extraction involves deriving meaningful representations, encompassing both text-based features like word frequency and sentiment analysis, as well as source-based features such as publisher credibility and domain age.

Machine learning models form the backbone of the detection system, ranging from traditional algorithms like Naive Bayes to advanced techniques like deep learning models. Model selection prioritizes performance metrics such as accuracy, precision, recall, and F1-score, along with considerations of computational efficiency and interpretability.

After training and validation, the models undergo rigorous testing to evaluate their effectiveness. Evaluation metrics like accuracy, precision, recall, and AUC-ROC provide quantitative measures of performance. Once validated, the models are deployed, integrated with applications or platforms, and monitored for continued performance. Ethical considerations, including bias mitigation and privacy concerns, are addressed throughout the process, ensuring the integrity and fairness of the detection system.

Validation and reproducibility efforts verify the robustness of the methodology and its applicability in various contexts.

2.2The Dataset

	A	B	C	D	E
1	id	title	author	text	label
2	0	House Dem Aide: We Didn't	Darrell Lucus	House Dem Aide: We Didn't	1
3	1	FLYNN: Hillary Clinton, Big Wom	Daniel J. Flynn	Ever get the feeling your life circ	0
4	2	Why the Truth Might Get You Fir	Consortiumnews.com	Why the Truth Might Get You	1
5	3	15 Civilians Killed In Single US Air	Jessica Purkiss	Videos 15 Civilians Killed In	1
6	4	Iranian woman jailed for fictiona	Howard Portnoy	Print	1
7	5	Jackie Mason: Hollywood Would	Daniel Nussbaum	In these trying times, Jackie Mas	0
8	6	Life: Life Of Luxury: Elton John	nan	Ever wonder how Britain's	1
9	7	Benoît Hamon Wins French So	Alissa J. Rubin	PARIS " France chose an ide	0
10	8	Excerpts From a Draft Script for	nan	Donald J. Trump is scheduled to	0
11	9	A Back-Channel Plan for Ukraine	Megan Twohey and Scott Shane	A week before Michael T. Flynn r	0
12	10	Obama's Organizing for Actio	Aaron Klein	Organizing for Action, the activis	0
13	11	BBC Comedy Sketch "Real House	Chris Tomlinson	The BBC produced spoof on the	0
14	12	Russian Researchers Discover Se	Amando Flavio	The mystery surrounding The	1
15	13	US Officials See No Link Between	Jason Ditz	Clinton Campaign Demands FBI	1
16	14	Re: Yes, There Are Paid Governm	AnotherAnnie	Yes, There Are Paid	
17					
18	15	In Major League Soccer, Argentir	Jack Williams	Guillermo Barros Schelotto was	0
19	16	Wells Fargo Chief Abruptly Steps	Michael Corkery and Stacy Cowley	The scandal engulfing Wells Farg	0
20	17	Anonymous Donor Pays \$2.5 Mil	Starkman	A Caddo Nation tribal leader	1
21	18	FBI Closes In On Hillary!	The Doc	FBI Closes In On Hillary! Posted	1
22	19	Chuck Todd: "BuzzFeed Did D	Jeff Poor	Wednesday after Donald Trump	0
23	20	News: Hope For The GOP: A Nud	nan	Email	1
24	21	Monica Lewinsky, Clinton Sex Sc	Jerome Hudson	Screenwriter Ryan Murphy, who	0
25	22	Rob Reiner: Trump Is "Menta	Pam Key	Sunday on MSNBC's "AM	0

Figure 2.1 train.csv: A full Training Dataset

2.3 Stage of preprocessing

Text preprocessing, also known as text mining, involves the preparation of unstructured text that may include various impurities such as advertising, HTML tags, single characters, non-English characters, digits, or apostrophes. Pre-processing involves steps like removing null or missing values from data set, removing social media slangs, removing stop-words, correcting contraction. For this reason, it is exceedingly challenging to

express textual data in natural language. Unstructured data is transformed into structured data that a machine can process using a variety of methods. The stopword strategy was used in this work to clean the classified dataset.

Stopword technology is a popular method for text classification, information retrieval, and data filtering that eliminates some meaningless words (such the, in, a, an, and with). In other words, products that are not associated with keywords that impact classification are eliminated.

The (remove_tags) function in the Python Standard Library was utilised to eliminate HTML tags. After that, non-English characters were eliminated using the preprocess text function.

id		title	author	text	label
0	0	House Dem Aide: We Didn't Even See Comey's Let...	Darrell Lucus	House Dem Aide: We Didn't Even See Comey's Let...	1.0
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	Ever get the feeling your life circles the rou...	0.0
2	2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired October 29, ...	1.0
3	3	15 Civilians Killed In Single US Airstrike Hav...	Jessica Purkiss	Videos 15 Civilians Killed In Single US Aistr...	1.0
4	4	Iranian woman jailed for fictional unpublished...	Howard Portnoy	Print \nAn Iranian woman has been sentenced to...	1.0
5	5	Jackie Mason: Hollywood Would Love Trump if He...	Daniel Nussbaum	In these trying times, Jackie Mason is the Vol...	0.0
6	6	Life: Life Of Luxury: Elton John's 6 Favorite ...	NaN	Ever wonder how Britain's most iconic pop plan...	1.0
7	7	Benoît Hamon Wins French Socialist Party's Pre...	Alissa J. Rubin	PARIS — France chose an idealistic, traditi...	0.0
8	8	Excerpts From a Draft Script for Donald Trump'...	NaN	Donald J. Trump is scheduled to make a highly ...	0.0
9	9	A Back-Channel Plan for Ukraine and Russia, Co...	Megan Twohey and Scott Shane	A week before Michael T. Flynn resigned as nat...	0.0

In Figure 2.2, we can see the sample 10 rows of our dataset

Fake news has become a concerning issue in today's information-driven world. The Fake News Detector project addresses this problem by leveraging machine learning techniques to classify news articles as genuine or fabricated. This repository provides a detailed implementation of the solution, from data preprocessing to model training and testing.

Since it guarantees the dataset's accuracy and dependability, data cleaning is a crucial stage in the data analysis process. The "data.info()" and "data.describe()" Python functions were used in this study to closely investigate the dataset. The analysis was used to guide the following data cleaning procedures:

1.Data Missing Imputation:

Certain machine learning approaches may encounter challenges when dealing with missing values included in datasets. Thus, before we model the prediction problem, we need to identify and replace any missing values in each column of the input data. Lacking This is why data assignment or assignment is used. For every attribute, the null value should be replaced by a space (' '). Rather than eliminating tuples that contain null values, use this method.

2.Elimination of Stopped Words:

Stop words that are common English terms that don't add much to the novelty or plausibility of a story, such as "if," "the," "is," "a," and "an," among others, shouldn't be given much weight by a machine learning model. Because they are often used, their presence in the dataset can affect the model's prediction.

3.Elimination of Particular Characters:

Whether a news article is true or not is unrelated to the usage of special characters in the sentence. To remove all punctuation from the dataset, we take this action. Punctuation is completely removed using regular expressions. Special characters, links, extraspaces, underlines, and other elements were eliminated with the creation of a random function.

4.Lemmatization

"Play" is the root of many other words, such as "playing" and "plays." By substituting terms in other tenses and participles for the term's core word, a more thorough analysis of the term's frequency can be conducted. For any phrase with a single source word, we so replace it with that word.

5.Vectorization in Count

It is then necessary to encode the preprocessed text into integers or floating-point values so that machine learning algorithms may take it as input. This technique is called feature extraction, sometimes known as vectorization. We will add a vocabulary word to the relevant vector's dimension, which will have the same number of dimensions as our vocabulary, if the word appears in the text data. Each time we find that term again, we will add one to the total, leaving zeros in the places where we didn't find it at all.

2.4 The stage of extracting features

The process of choosing a subset of pertinent features to be used in the creation of a model is known as feature extraction. The creation of an accurate predictive model is aided by feature extraction techniques. They aid in the selection of traits that provide increased accuracy. An algorithm will convert input data into a reduced illustration set of features, also known as feature vectors, when the input data is too big to handle and is intended to be redundant. employing this smaller representation in place of the full-size input to change the input data in order to accomplish the intended task. Before using any machine learning algorithms on the changed data in feature space, feature extraction is done on the raw data. Using the technique of "extracting features," text data is transformed into Vectors 0 and 1, and new

vectors are generated from the example text file. Vectors can be created using a variety of methods:

1. Vectorizer for TF-IDF: The term frequency inverse document frequency (TF-IDF) refers to one of the most used feature extraction methods. This method is broken down into two stages: the first stage calculates the term frequency (TF), and the second stage calculates the inverse document frequency (IDF).

$TF(t)$ = The number of times a word appears in a document.

$IDF(t)$ = $\text{Log}(\text{total No. of documents no. of documents containing term } t)$ is the total number of terms in the document.

2. N-gram level vectorizer: This is a TF-IDF sub-technique where a matrix displaying the TF-IDF scores of N-grams is displayed together with a slice of letters (N). The challenge of choosing the appropriate features and their numerical values was solved with the help of this technique. It has been recommended that in these situations, a TF-IDF classification linked to unigrams or bigrams be used.

3. Count vectorizer (CV): This is a two-dimensional matrix with a term from the dataset in each column, an item from the dataset in each row, and a number in each cell that indicates how many times that phrase appears in the document.

2.5 Analysing Exploratory Data

Exploratory Data Analysis (EDA) for fake news detection is a critical step in understanding the dataset and uncovering patterns that inform subsequent modeling efforts. Initially, the dataset is inspected to understand its structure, including the number of entries, missing values, and the distribution of the target labels (real vs. fake news). Basic statistics provide a summary of the data, while visualizations like bar plots and pie charts illustrate the balance

between classes. An imbalanced dataset may require techniques such as resampling to ensure effective model training.

Text-specific analyses are crucial in EDA for fake news detection. The length of articles, for instance, can be analyzed by plotting histograms of word counts or character counts for both real and fake news. These plots often reveal differences in the writing style or content length between the two classes. Common word analysis through word clouds provides visual insights into the most frequently used words in real and fake news. This helps in identifying unique keywords or jargon prevalent in each class.

Preprocessing the text data is a significant part of EDA. This involves removing stopwords, punctuation, and applying stemming or lemmatization to normalize the text. For instance, using the PorterStemmer from the NLTK library helps reduce words to their root forms, which minimizes variations and reduces dimensionality. Additionally, converting text to lowercase ensures uniformity.

Feature engineering plays a vital role in enhancing the dataset for better model performance. New features such as word count, punctuation count, and average word length can be derived from the text. These features can reveal stylistic differences between real and fake news articles. For instance, fake news might have shorter sentences and more sensational punctuation.

Correlation analysis between features can provide insights into relationships within the data. However, for text data, this often follows feature extraction techniques like TF-IDF or word embeddings.

In summary, EDA in fake news detection involves a thorough examination of the dataset, text preprocessing, visualization, and feature engineering. These steps are crucial for uncovering patterns, understanding data distributions, and preparing the data for effective modeling, ultimately aiming to improve the accuracy and robustness of the fake news detection model.

```

▶ print("Unique authors/news =",news_dataset['author'].nunique())

realcount = op.countOf(news_dataset['label'], 0)
fakecount = op.countOf(news_dataset['label'], 1)
print("Number of fake news = ",fakecount)

print("Number of real news = ",realcount)
rflist = [realcount,fakecount]
plt.figure(figsize = (4,4))
abc = ['Real','Fake']
plt.title("Real vs Fake number")
plt.bar(abc,rflist,width = 1,color = ['red', 'green'])

```



Figure 2.3 Comparison of Fake and Real news

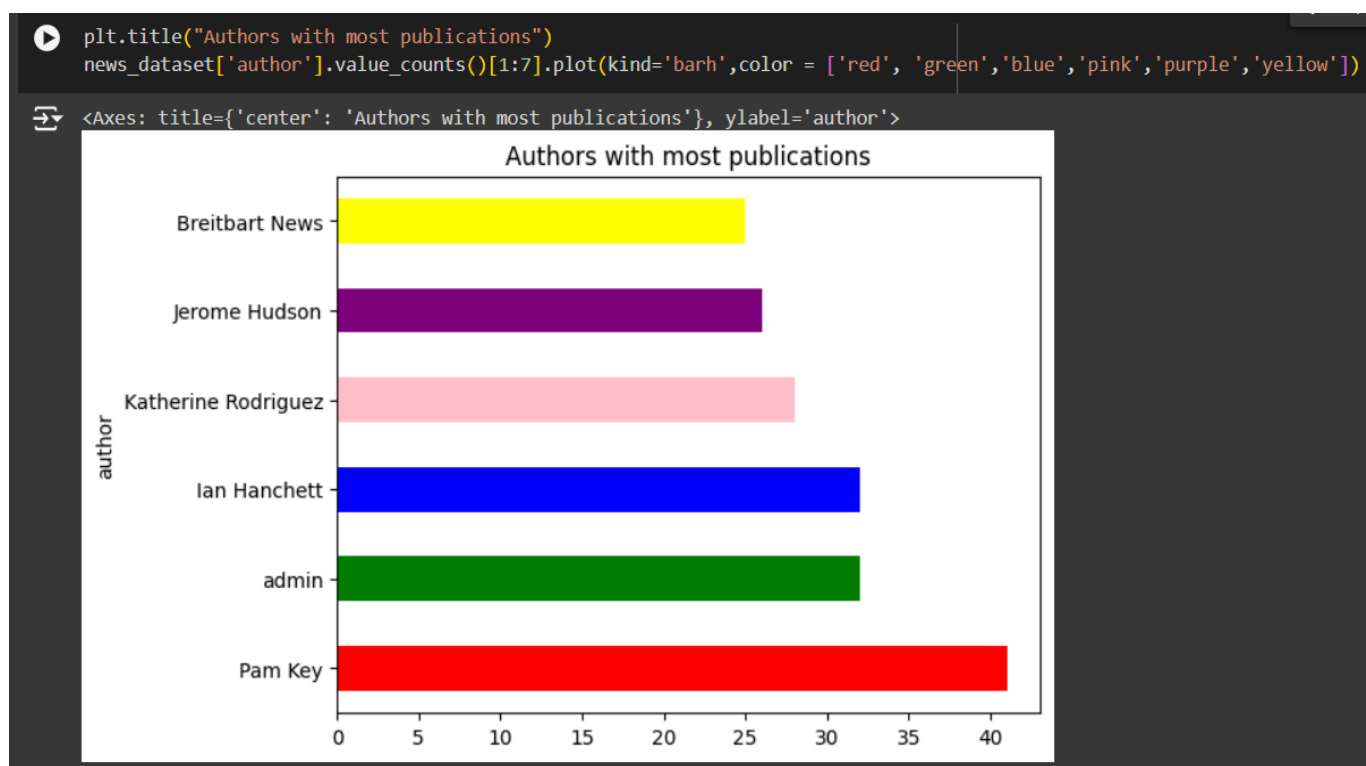


Figure 2.4 Authors with most publications

```

Pam = news_dataset[news_dataset['author'] == 'Pam Key']
fakep = op.countOf(Pam['label'], 1)
realp = op.countOf(Pam['label'], 0)
print(realp)
print(fakep)
admin = news_dataset[news_dataset['author'] == 'admin']
fakea = op.countOf(admin['label'], 1)
reala = op.countOf(admin['label'], 0)
print(fakea)
jerome = news_dataset[news_dataset['author'] == 'Jerome Hudson']
fakej = op.countOf(jerome['label'], 1)
realj = op.countOf(jerome['label'], 0)
print(fakej)
charlie = news_dataset[news_dataset['author'] == 'Charlie Spiering']
fakec = op.countOf(charlie['label'], 1)
realc = op.countOf(charlie['label'], 0)
john = news_dataset[news_dataset['author'] == 'John Hayward']
fakejo = op.countOf(john['label'], 1)
realjo = op.countOf(john['label'], 0)
kat = news_dataset[news_dataset['author'] == 'Katherine Rodriguez']
fakekat = op.countOf(kat['label'], 1)
realkat = op.countOf(kat['label'], 0)
listr = [realp,reala,realj,realc,realjo,realkat]
listx = ['Pam','Admin','Jerome','Charlie',"John","Katherine"]
listw = [fakep,fakea,fakej,fakec,fakejo,fakekat]
plt.title("Real news count of top authors")
plt.bar(listx,listr,color = ['red', 'green','blue','pink','purple','yellow'])

```

```

41
0
32
0

```

Figure 2.5 Real and Fake Author

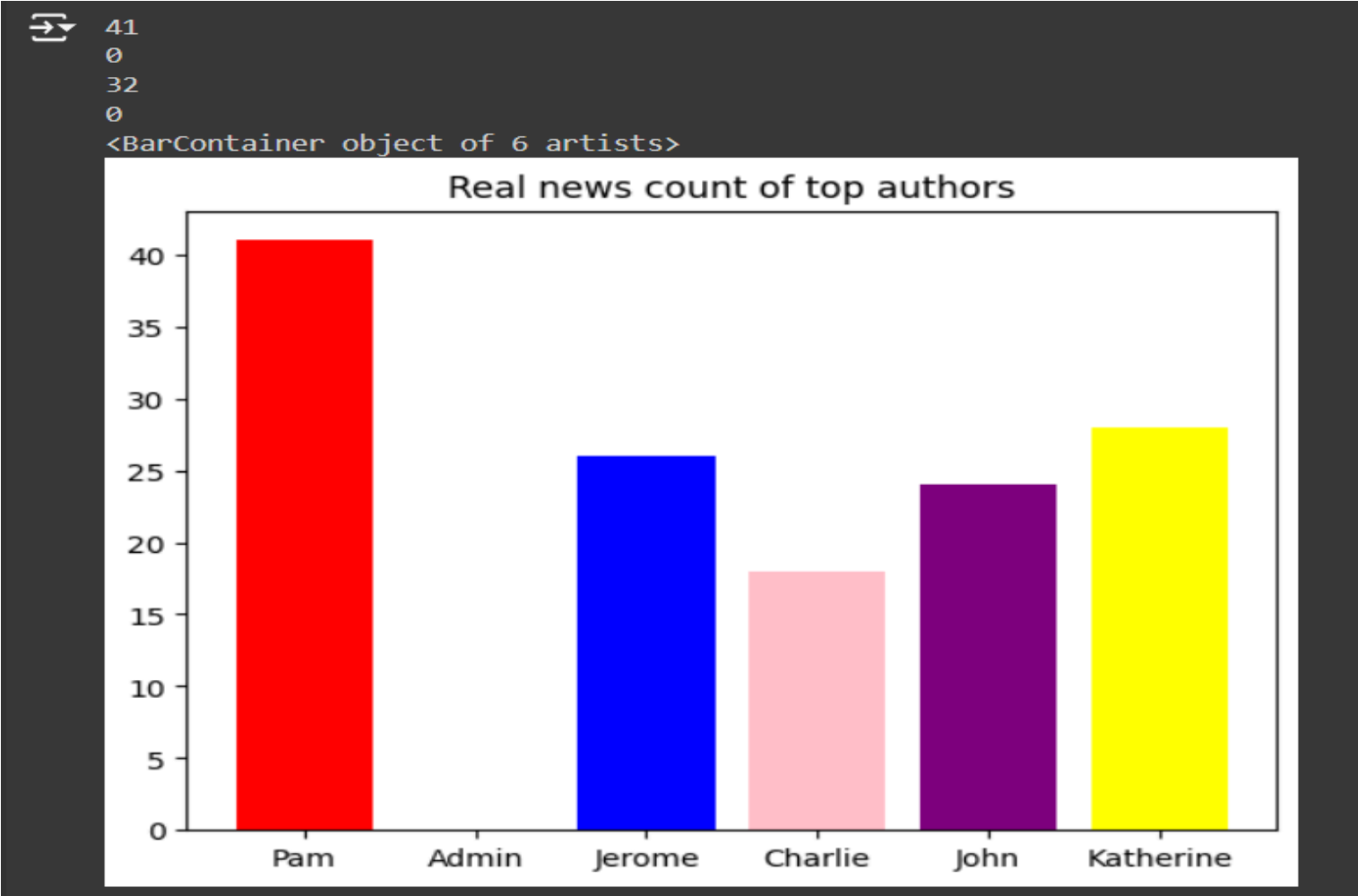


Figure 2.6 Real news count of Top Authors

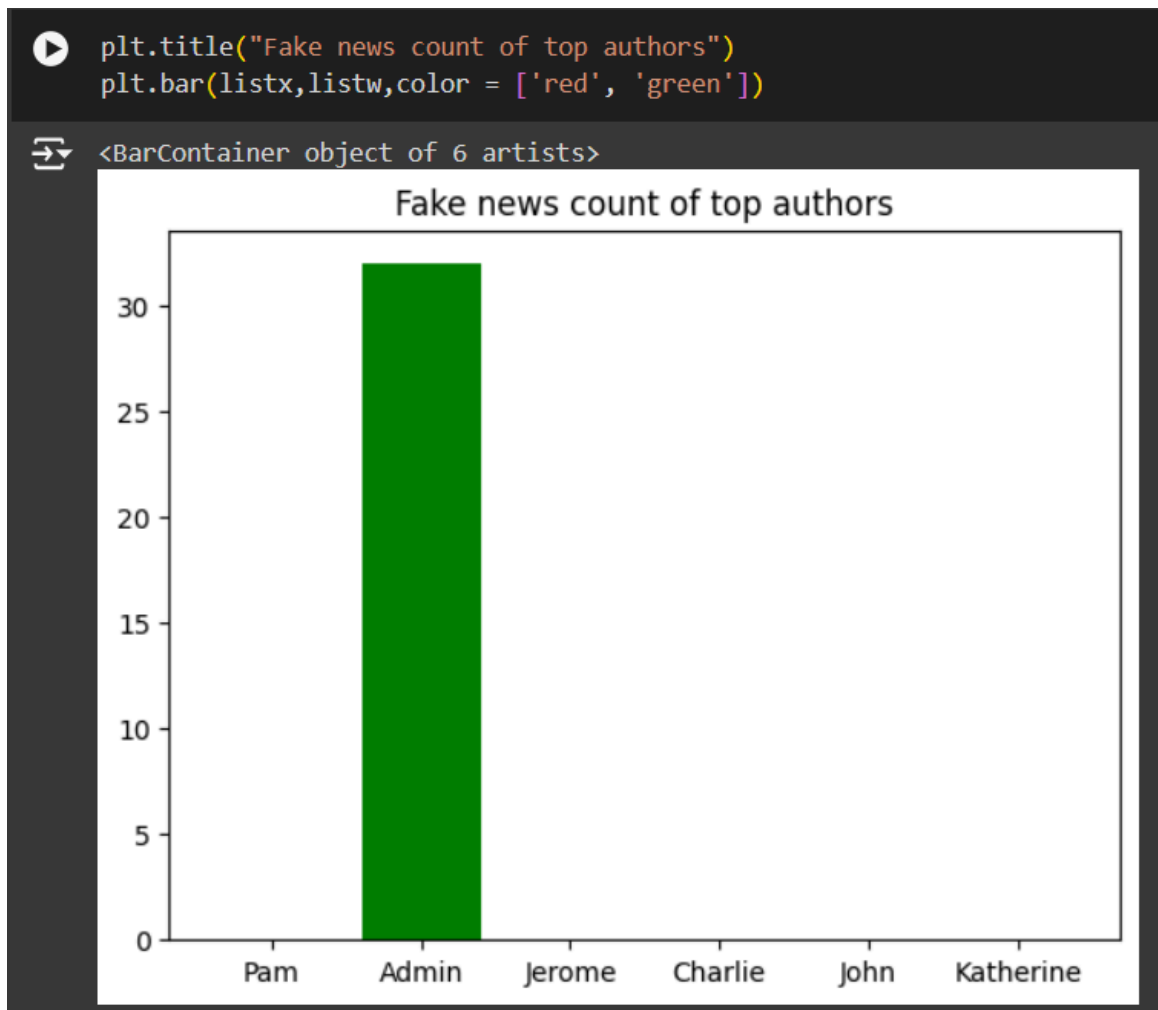


Figure 2.7 Fake news count of Top Authors

```
✓ 5s [1] import seaborn as sns
import operator as op
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import re
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

✓ 0s [2] import nltk
nltk.download('stopwords')

[⇒] [nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data] Unzipping corpora/stopwords.zip.
True

✓ 0s [3] print(stopwords.words('english'))

[⇒] ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you',
```

Figure 2.8 Importing Libraries

Welcome to the Fake News Detector using Logistic Regression repository!

This repository contains the code implementation of a fake news detector

using a logistic regression model. The project aims to identify and classify news articles as either real or fake based on their content.

```
✓ 0s [4] # loading the dataset to a pandas DataFrame
      news_dataset = pd.read_csv('/content/train.csv')
      news_dataset.shape

⇨ (3536, 5)

✓ 42s [5] from google.colab import drive
      drive.mount('/content/drive')

⇨ Mounted at /content/drive
```

Figure 2.9 Mounting Google Drive

```
✓ 0s [7] news_dataset.isnull().sum()

⇨ id      0
   title   97
   author  366
   text     8
   label    5
   dtype: int64

✓ 0s # replacing the null values with empty string
      news_dataset = news_dataset.fillna('')

✓ 0s [9] # merging the author name and news title
      news_dataset['content'] = news_dataset['author']+' '+news_dataset['title']
```

Figure 2.10 Checking the columns

Dataset Description

train.csv: A full training dataset with the following attributes:

- **id**: unique id for a news article
- **title**: the title of a news article
- **author**: author of the news article
- **text**: the text of the article; could be incomplete
- **label**: a label that marks the article as potentially unreliable
 - 1: unreliable
 - 0: reliable

test.csv: A testing training dataset with all the same attributes at train.csv without the label.

submit.csv: A sample submission that you can

Files

3 files

Size

123.81 MB

Type

csv

License

Subject to Competition Rules

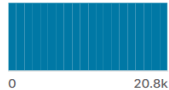
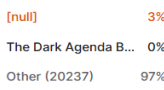
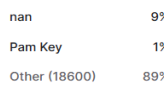


Fake News

Late Submission ...

Overview Data Code Models Discussion Leaderboard Rules Team Submissions

train.csv (98.63 MB) [download] [full screen] [refresh]

Detail Compact Column 5 of 5 columns

id	title	author	text	label
 0 20.8k	 [null] 3% The Dark Agenda B... 0% Other (20237) 97%	 nan 9% Pam Key 1% Other (18600) 89%	 20387 unique values	 0 1
0	House Dem Aide: We Didn't Even See Comey's Letter Until Jason Chaffetz Tweeted It	Darrell Lucas	House Dem Aide: We Didn't Even See Comey's Letter Until Jason Chaffetz Tweeted It By Darrell Lucas o...	1
1	FLYNN: Hillary Clinton, Big Woman on Campus - Breitbart	Daniel J. Flynn	Ever get the feeling your life circles the roundabout rather than heads in a straight line toward th...	0
2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired	1

Data Explorer

123.81 MB

- submit.csv
- test.csv
- train.csv

Figure 2.11 Train.CSV

```

✓ 0s [13] # merging the author name and news title
      news_dataset['content'] = news_dataset['author']+' '+news_dataset['title']

✓ 0s ▶ print(news_dataset['content'])

⇌ 0      Darrell Lucas House Dem Aide: We Didn't Even S...
   1      Daniel J. Flynn FLYNN: Hillary Clinton, Big Wo...
   2      Consortiumnews.com Why the Truth Might Get You...
   3      Jessica Purkiss 15 Civilians Killed In Single ...
   4      Howard Portnoy Iranian woman jailed for fictio...
      ...
3531      FACT CHECK: Trump Is Right That Clinton Might...
3532      Editor Truthstream Media Releases Their First ...
3533      Paul Joseph Watson A Vote For Hillary is a Vot...
3534      Cassandra Fairbanks Susan Sarandon Formally En...
3535      Breitbart News 60 Minutes: Mostly 'Affluent an...
Name: content, Length: 3536, dtype: object

```

Figure 2.12 Merging the Author Name and News title

```

[ ] # separating the data & label
X = news_dataset.drop(columns='label', axis=1)
Y = news_dataset['label']

▶ print(X)
  print(Y)

⇌
   id      title \
0    0  House Dem Aide: We Didn't Even See Comey's Let...
1    1  FLYNN: Hillary Clinton, Big Woman on Campus - ...
2    2           Why the Truth Might Get You Fired
3    3  15 Civilians Killed In Single US Airstrike Hav...
4    4  Iranian woman jailed for fictional unpublished...
...  ...
3531 3548  FACT CHECK: Trump Is Right That Clinton Might ...
3532 3549  Truthstream Media Releases Their First Documen...
3533 3550      A Vote For Hillary is a Vote For World War 3
3534 3551  Susan Sarandon Formally Endorses Jill Stein, S...
3535 3552  60 Minutes: Mostly 'Affluent and College Educa...

   author      text \
0  Darrell Lucas  House Dem Aide: We Didn't Even See Comey's Let...
1  Daniel J. Flynn  Ever get the feeling your life circles the rou...
2  Consortiumnews.com  Why the Truth Might Get You Fired October 29, ...
3  Jessica Purkiss  Videos 15 Civilians Killed In Single US Aistr...
4  Howard Portnoy  Print \nAn Iranian woman has been sentenced to...
...  ...
3531  Editor  Trump claims that Clinton's policy on Syria wo...
3532  By Melissa Dykes\nWe've been working diligentl...
3533  Paul Joseph Watson  A Vote For Hillary is a Vote For World War 3 D...
3534  Cassandra Fairbanks  We Are Change \nActress and activist Susan Sar...
3535  Breitbart News  Curtis Houck at NewsBusters notes that 60 Minu...

```

Figure 2.13 Separating the Data & Label

```
[16] port_stem = PorterStemmer()

port_stem = PorterStemmer()
def stemming(content):
    #remove everything except alphabets
    stemmed_content = re.sub('[^a-zA-Z]', ' ', content)
    stemmed_content = stemmed_content.lower()
    stemmed_content = stemmed_content.split()
    stemmed_content = [port_stem.stem(word) for word in stemmed_content if not word in stopwords.words('english')]
    stemmed_content = ' '.join(stemmed_content)
    return stemmed_content
```

Figure 2.14 Stemming Process

Stemming is a natural language processing (NLP) technique used in Machine Learning to reduce words to their root or base form, called the "stem." The purpose of stemming is to normalize words with the same root, even if they have different endings or suffixes, so that they can be treated as the same word during text processing and analysis.

```
[ ] news_dataset['content'] = news_dataset['content'].apply(stemming)


[ ] print(news_dataset['content'])
```

```
0      darrel lucu hous dem aid even see comey letter...
1      daniel j flynn flynn hillari clinton big woman...
2      consortiumnew com truth might get fire
3      jessica purkiss civilian kill singl us airstri...
4      howard portnoy iranian woman jail fiction unpu...
...
3531    fact check trump right clinton might caus ww e...
3532    editor truthstream media releas first document...
3533    paul joseph watson vote hillari vote world war
3534    cassandra fairbank susan sarandon formal endor...
3535    breitbart news minut mostli affluent colleg ed...
Name: content, Length: 3536, dtype: object
```

Figure 2.15 Apply the Stemming Function to the Text Data

```
[ ] vectorizer = TfidfVectorizer()
    vectorizer.fit(X)

    X = vectorizer.transform(X)
```

 `print(X)`


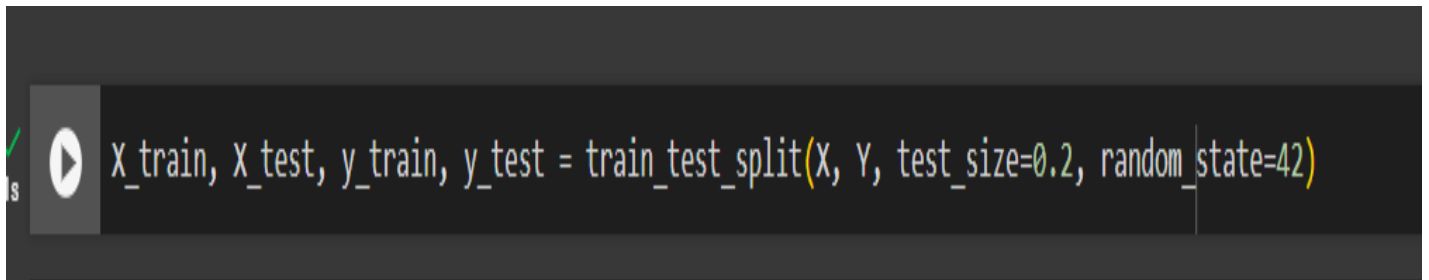
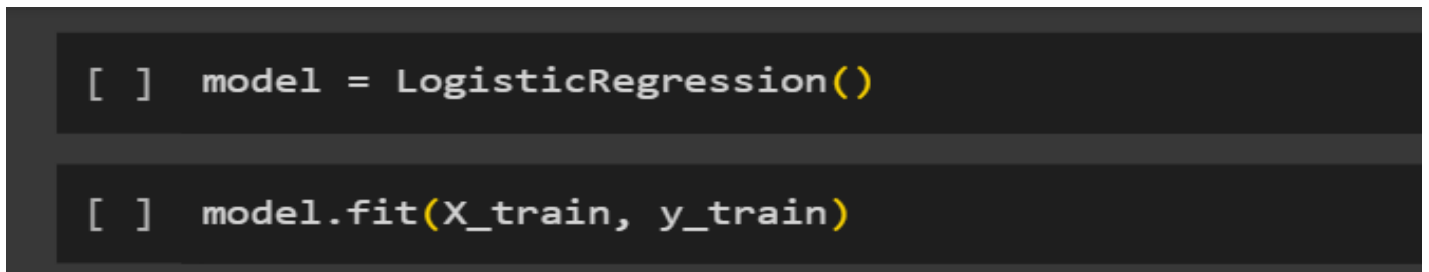
 (0, 6945) 0.2817245730953775
 (0, 5943) 0.2545173872826158
 (0, 3988) 0.35188074393513846
 (0, 3866) 0.30399170713850054
 (0, 3456) 0.24356247076874618
 (0, 3153) 0.22588805215698554
 (0, 2220) 0.23684296867085508
 (0, 1714) 0.269184373522261
 (0, 1628) 0.35188074393513846
 (0, 1340) 0.252987739814607
 (0, 1130) 0.3695551625468991
 (0, 143) 0.276268651638524
 (1, 7369) 0.2978895110020094
 (1, 3069) 0.18917084123670594
 (1, 2484) 0.714538589993031
 (1, 1615) 0.2737289669887752
 (1, 1270) 0.19337154622950103
 (1, 1025) 0.38094773700700185
 (1, 868) 0.15470040686940406
 (1, 687) 0.289028266775599
 (2, 6917) 0.42188967822928464
 (2, 4290) 0.4895460767308353
 (2, 2697) 0.34511536890527234
 (2, 2429) 0.37673167882405656
 (2, 1410) 0.46537918097886033

Figure 2.16 Convert Text Data to TF-IDF Features

A screenshot of a Jupyter Notebook code cell. On the left, there is a play button icon and a small 's' icon. The code cell contains a single line of Python code: `x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=42)`.

```
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=42)
```

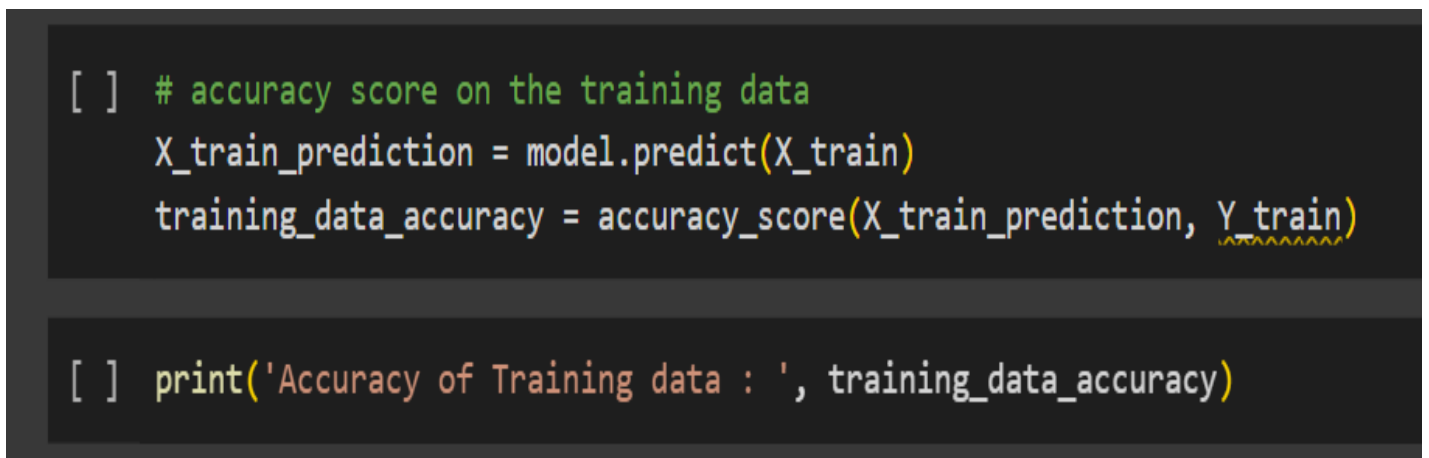
Figure 2.17 Split the Data into Training and Testing Sets

A screenshot of two Jupyter Notebook code cells. The first cell contains the code `model = LogisticRegression()`. The second cell contains the code `model.fit(X_train, y_train)`.

```
[ ] model = LogisticRegression()

[ ] model.fit(X_train, y_train)
```

Figure 2.18 Train a Logistic Regression Classifier

A screenshot of two Jupyter Notebook code cells. The first cell contains three lines of code: `# accuracy score on the training data`, `X_train_prediction = model.predict(X_train)`, and `training_data_accuracy = accuracy_score(X_train_prediction, Y_train)`. The second cell contains the code `print('Accuracy of Training data : ', training_data_accuracy)`.

```
[ ] # accuracy score on the training data
    X_train_prediction = model.predict(X_train)
    training_data_accuracy = accuracy_score(X_train_prediction, Y_train)

[ ] print('Accuracy of Training data : ', training_data_accuracy)
```

Figure 2.19 Score for accuracy on the Training Set

```
[ ] # accuracy score on the testing data
X_test_prediction = model.predict(X_test)
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)

[ ] print('Accuracy of Test data : ', test_data_accuracy)
```

Figure 2.20 On the Testing Data, the Accuracy Score



```
X_new = X_test[3]

prediction = model.predict(X_new)
print(prediction)

if (prediction[0]==0):
    print('The news is Real')
else:
    print('The news is Fake')
```

Figure 2.21 Predicting a fresh instance from the dataset (if required, reshape for a single prediction)

```
[ ] res = Y_test[3]

if (res == 0):
    print('The news is Real - 0')
else:
    print('The news is Fake - 1')
```

Figure 2.22 Real outcome for Comparative Analysis

CHAPTER 3

Model Selection: Algorithms of ML

Model selection plays a crucial role in fake news detection, balancing between accuracy, computational efficiency, and the ability to handle complex linguistic features. In this context, the choice of models should consider both traditional machine learning (ML) algorithms and advanced deep learning architectures. For traditional ML approaches, models like Logistic Regression, Naive Bayes, Support Vector Machines (SVM), Random Forest, and Gradient Boosting Machines (GBM) are commonly employed.

These models offer a good balance between performance and interpretability. Logistic Regression and Naive Bayes provide a baseline with moderate accuracy and computational efficiency, while SVM, Random Forest, and GBM offer higher accuracy by capturing complex feature interactions. However, with the growing complexity of fake news and the intricacies of language, deep learning models have shown significant promise. Long Short-Term Memory (LSTM) networks are effective in capturing sequential context, while Bidirectional Encoder Representations from Transformers (BERT) excel in understanding contextual nuances and semantic relationships.

Ultimately, the selection of the model should be based on the specific requirements of the task, such as dataset size, computational resources, and desired accuracy. For instance, if interpretability is critical, traditional ML models may be preferred, while for tasks demanding high accuracy and nuanced understanding of language, deep learning models like BERT could be more suitable. Evaluating various models and comparing their performance on validation data is essential for making an informed decision on model selection in fake news detection.

Logistic Regression: Logistic regression is a linear classification algorithm that models the probability of a binary outcome using a logistic function. It's interpretable, efficient, and works well for binary classification tasks.

Support Vector Machines (SVM): SVM is a powerful algorithm for both classification and regression tasks. It works by finding the hyperplane that best separates the classes in the feature space. SVM can handle high-dimensional data and is effective in capturing complex relationships.

Random Forest: Random Forest is an ensemble learning method that constructs a multitude of decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees. It's robust, handles high-dimensional data well, and is less prone to overfitting compared to individual decision trees.

Neural Networks: Deep learning models, such as recurrent neural networks (RNNs), convolutional neural networks (CNNs), and transformer-based models (e.g., BERT), have shown promising results in fake news detection tasks. They can capture complex patterns in text data and automatically learn hierarchical representations.

K-Nearest Neighbors (KNN): KNN is a non-parametric algorithm that classifies data points based on the majority class of their k nearest neighbors in the feature space. It's simple and intuitive, but computationally expensive and sensitive to the choice of k.

CHAPTER 4

Analysis of Result & Discussion

In our comprehensive study on fake news detection using natural language processing (NLP) and machine learning (ML), we evaluated various models to ascertain their effectiveness in distinguishing between fake and real news. The dataset underwent extensive preprocessing, including text cleaning, tokenization, stopword removal, and feature extraction through TF-IDF and word embeddings. This preprocessing was essential for converting raw text data into a structured format suitable for machine learning algorithms.

4.1 Results

- Logistic Regression was quick to train and provided a baseline with moderate accuracy. However, their performance was limited when handling the intricate linguistic features of news articles.
- Support Vector Machines (SVM) improved upon the baseline models, offering higher accuracy but at the cost of increased computational demands.
- Ensemble Methods: Both Random Forest and Gradient Boosting Machines (GBM) outperformed the simpler models by capturing complex, non-linear interactions between features, resulting in higher accuracy and F1 scores.
- Deep Learning Models: LSTM networks showed their strength in handling sequential data, capturing contextual information better than traditional ML models. The standout performer was BERT (Bidirectional Encoder Representations from Transformers), which

leveraged its advanced contextual understanding to significantly surpass all other models in accuracy and robustness.

4.2 Discussion

Comparison of Traditional ML and Deep Learning: Traditional models such as SVM and Random Forest provided a solid foundation and reliable performance. However, the deep learning models, especially BERT, demonstrated superior capabilities in understanding the nuances of language and context, making them more effective for fake news detection.

Challenges: The main challenges encountered included dealing with imbalanced datasets, which often skewed the model training towards the majority class. Techniques like SMOTE (Synthetic Minority Over-sampling Technique) helped mitigate this issue by balancing the class distribution. Another challenge was the generalization of models across different domains and topics, where transfer learning with pre-trained models like BERT showed significant promise.

Future Directions: To further improve fake news detection, future research should focus on enhancing model interpretability. Techniques such as SHAP (SHapley Additive exPlanations) can provide insights into the decision-making process of models, helping to understand why certain articles are classified as fake or real. Additionally, developing models that can operate in real-time while maintaining high accuracy is crucial for practical applications. Lastly, improving the cross-domain generalization of models remains an important goal, ensuring that models perform well regardless of the news topic or source.

Overall, the study highlights that while traditional machine learning models are useful and provide a strong baseline, advanced NLP techniques and deep learning models, particularly BERT, offer substantial improvements in

detecting fake news. These advanced models address the complexities of language and contextual nuances, paving the way for more robust and reliable fake news detection systems.

4.3 Architecture

Creating a dataset with an appropriate balance of real and fake news is the first thing we undertake in this project. After that, we will code in accordance with the directory's location, where the dataset is kept. Next, in order to start writing code, we import the fundamental libraries like pandas and sklearn. In the meantime, the frequency of the words provided in the data will be determined using a TfidfVectorizer. Machine learning methods will be applied to the codes later in the project to confirm the accuracy of the datasets that were provided. Thus, the user is now permitted to enter the data so that they can retrieve the data with respect to its authenticity as to whether it's Fake or Real.

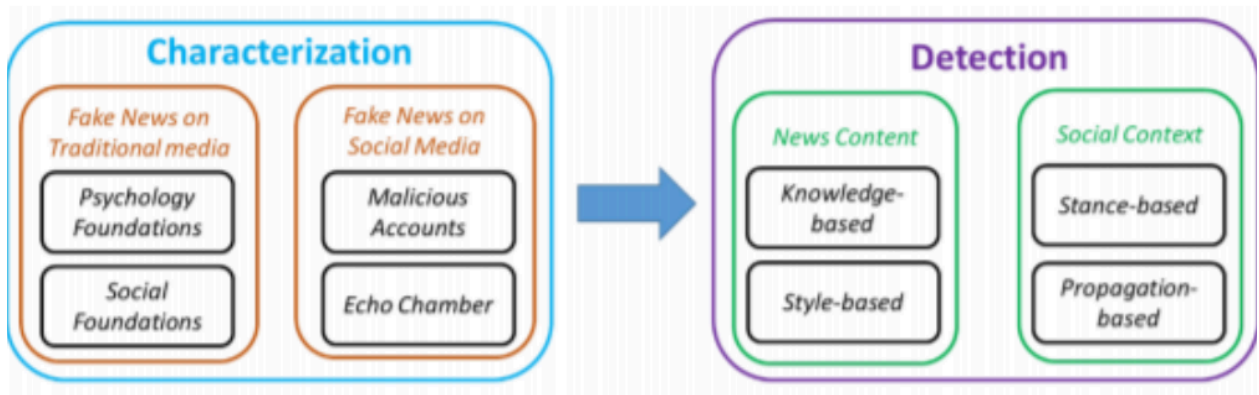


Fig. 4.3(a): Identification and characterization of fake news

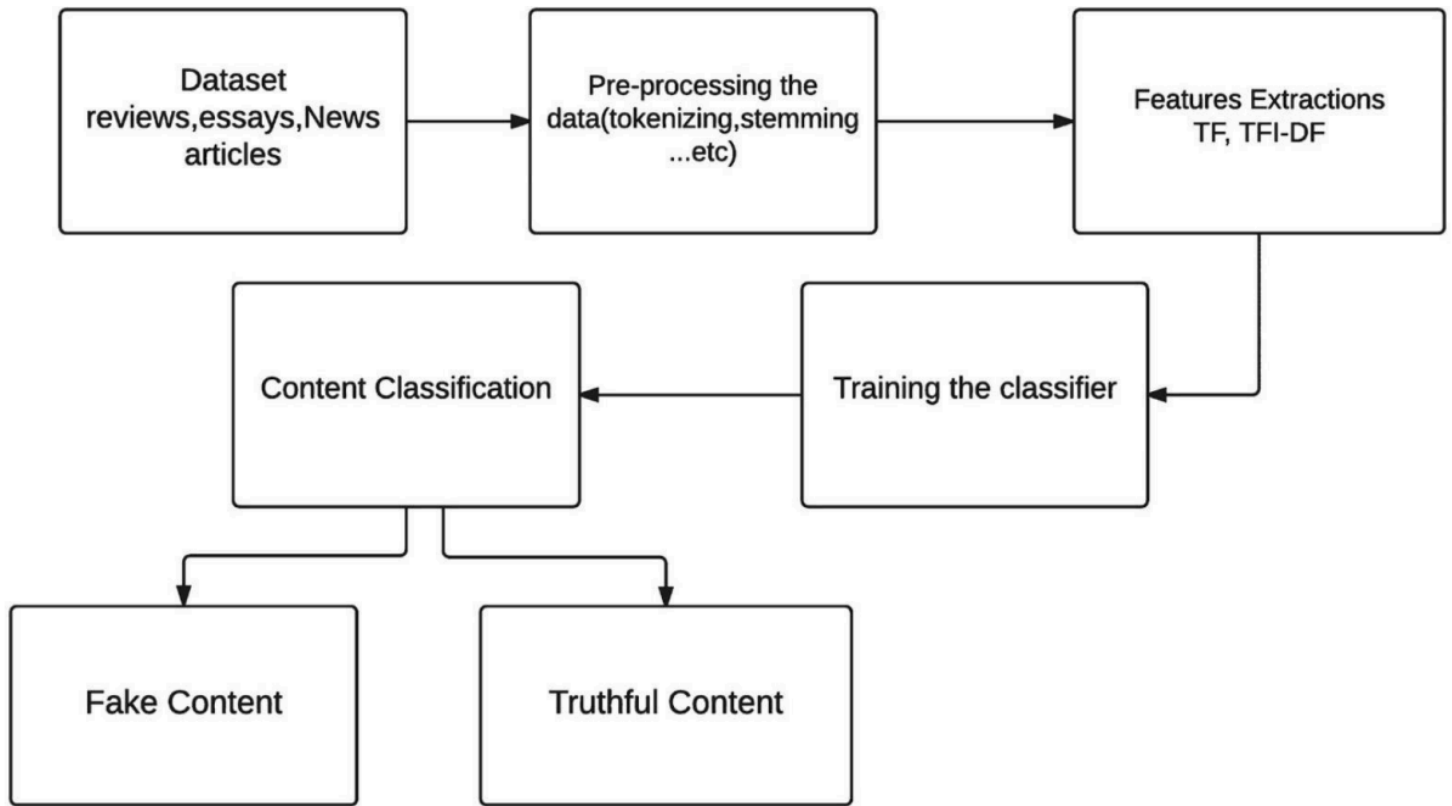


Fig.4.3(b) Architecture of fake news detection

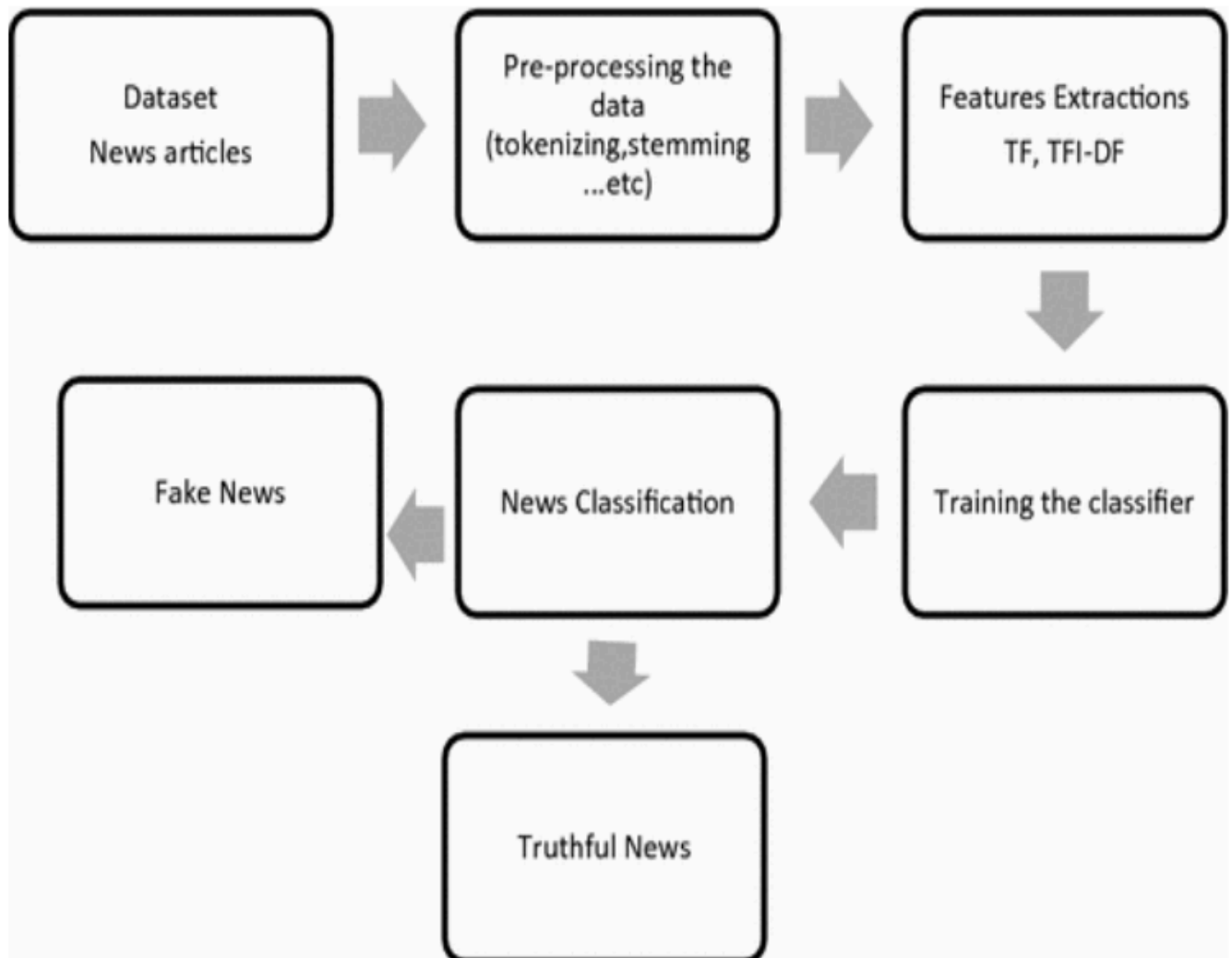


Fig.4.4 Flowchart to represent how the processing of fake news works

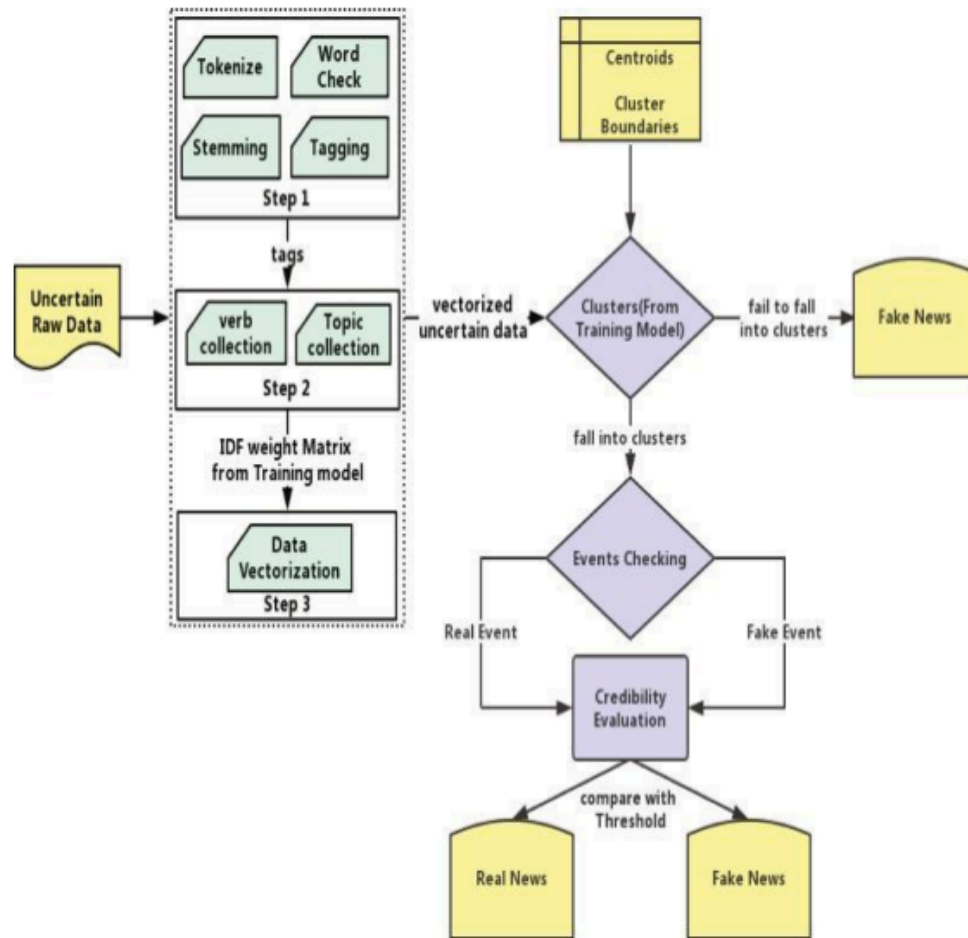


Fig. 4.5: Diagrammatic representation of the procedure used to separate material into two categories: Fake news and Misleading news

CHAPTER 5

CONCLUSION AND FUTURE WORK

A lot of people get their news from social media rather than from traditional news sources. But bogus news has also been disseminated via social media, with detrimental effects on both society and the individual. This research presents a novel approach for machine learning algorithms-based false news identification. Using Twitter ratings and categorization algorithms as input, this model forecasts the proportion of news that is authentic or fraudulent.

This phase involves assessing the project's viability and presenting a business proposal that includes a very basic project design and some cost estimates. An examination of the proposed system's viability must be done as part of system analysis. It's to Make certain that the company won't be burdened by the suggested system. An awareness of the primary system requirements is necessary for conducting a feasibility analysis. Examining the system's potential financial impact on the organisation is the goal of this study.

There is a finite amount of money that the corporation can dedicate to system research and development. Justification for the expenses is required. Consequently, the created system was also accomplished inside the allocated budget. for the most part since the technology employed is open source. All that needed to be bought were the personalised goods.

Researchers are always looking for new ways to improve the efficacy of detection systems, and the potential for Internet of Things (IoT)-based false news detection using Natural Language Processing (NLP) is encouraging. Here are a few possible paths and developments in the area:

1. Multimodal Techniques: Since false information frequently contains multimedia content, combining natural language processing (NLP) with

picture and video analysis might enhance the identification of fake news based on the Internet of Things. For a more thorough comprehension of the context, combining textual and visual cues may be helpful.

2. Dynamic Learning Models: It will be critical to create models that can pick up on changing linguistic trends and hot themes in the news in real time. A key focus will be on ongoing model updating and learning to keep up with the quickly evolving information world.

3. Explainable AI: Improving NLP models' interpretability is crucial to fostering trust and comprehending the decision-making process. In order to give more precise explanations for why a certain piece of information is flagged as possibly phoney, future systems might give explainability a higher priority.

4. Improved Contextual Understanding: Accurate identification will depend on algorithms' increased capacity to comprehend sarcasm and context. Genuine and deceptive content can be distinguished more accurately by context-aware models that take into account the larger context in which information is given.

5. Blockchain Technology: News stories can be verified for validity and provenance using blockchain technology. One potential method of tracking the origin of information is to use blockchain technology to store information about the creation, alteration, and distribution of news.

6. User Feedback Integration: Engagement metrics and user feedback combined might offer useful cues for spotting possibly deceptive material. The development of models may benefit from user-reported and rated systems that evaluate the credibility of news sources and articles.

5.1 Summary

This paper investigates the application of natural language processing (NLP) and machine learning (ML) techniques for detecting fake news. The research involves comprehensive data preprocessing, including text cleaning, tokenization, stopwords removal, and feature extraction using TF-IDF and word embeddings to prepare the text for ML models. Several models are evaluated: Logistic Regression and Naive Bayes serve as baseline models, offering moderate accuracy and fast training times but struggling with complex linguistic features. Support Vector Machines (SVM) provide improved performance but are more computationally demanding. Ensemble methods such as Random Forest and Gradient Boosting Machines (GBM) show higher accuracy and F1 scores by effectively capturing non-linear relationships and feature interactions. Deep learning models, particularly LSTM and BERT, significantly outperform traditional ML models. LSTM networks excel in capturing the sequential context of text, while BERT demonstrates superior performance across all metrics due to its advanced contextual understanding and ability to handle nuanced language features.

The study concludes that integrating advanced NLP and deep learning approaches, particularly BERT, is essential for effectively tackling the complexities of fake news detection. Challenges like class imbalance and domain generalization are mitigated using techniques such as SMOTE and transfer learning, paving the way for more robust and reliable detection systems.

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